

Introduction

Snowfall retrieval from space is one of the next important challenges for the hydro-meteorological communities. Due to ice scattering at higher frequencies (~ 85 GHz), high frequency radiometer channels are sensitive to frozen hydrometeors, resulting in reduction in brightness temperature with respect to clear air brightness temperature. A number of frozen precipitation retrievals algorithms have been reported in the past (e.g., Skofronick-Jackson et al. 2004). In general, snow retrieval is subject to uncertainties due to land surface emission ambiguities. Therefore, employing multi-frequency bands to extract both surface emissivity information from window channels (for AMSU-B/HMS these are 89, 150GHz) and water vapor information from water vapor channels (e.g., 183+/- 1 and 183+3 GHz) can mitigate uncertainties introduced by land surface during moist atmospheric conditions. Additional challenges are reduced signal from light and moderate snowfall events and also rapid (during precipitation event) and moderate (e.g., seasonal) changes in surface emissivity.

Developing snowfall detection and estimation algorithms, along with determining the detectability thresholds of falling snow over land covered surfaces using PMW-only observations, will continue to be a major challenge prior to the launch of the GPM core's in 2013.

The Canadian CloudSat/CALIPSO Validation Program (C3VP) field campaign provided a great opportunity to test and compare different approaches for precipitation detection (Skofronick-Jackson et al. 2008). Among those is the clustering approach based on the artificial neural networks, which is presented herein. The technique is applied to AMSU-B/HMS data with foot prints directly over the field near the city of Egbert, Ontario. The work described in this poster shows that indeed falling snow can be detected using 89, 150, and 183 GHz bands which will also be available onboard GPM Microwave Imager (GMI).

Field Campaign and Dataset

The Canadian CloudSat/CALIPSO Validation Program (C3VP) was a field campaign held from Oct. 31, 2006 through March 1, 2007. The C3VP field campaign provided an opportunity for the CloudSat/CALIPSO and Global Precipitation Measurement (GPM) mission teams to participate in cold-season northern latitude data collection activities. This created a great opportunity for NASA Instrumentation Sciences Branch to collect data for developing falling snow detection and snow rate retrieval algorithms. The C3VP field campaign was held at the Centre for Atmospheric Research Experiments (CARE, Fig. 1) research facility operated by the Air Quality Research Branch of the Meteorological Service of Canada. It is located 80 km north of Toronto, in a rural agricultural and forested region and has regular CloudSat and AMSU-B overpasses and was heavily instrumented (<http://www.c3vp.org/>).

The present study was conducted using more than 1300 co-located and temporally coincident AMSU-B/HMS TB and averaged-parisvel-precipitation-rate (with flag of snow or rain) data points over the CARE. The ground based Parisvels provided critical information on both detecting falling snow events as well as snow rates and made available from Oct 30, 2006 thru March 16, 2007.

Although MHS and AMSU-B are different in the channel lineup with channel 2 and channel 5 for MHS being 157 GHz and 190 GHz vs. for AMSU-B 150 GHz and 183 +/- 7 GHz, they were used fairly interchangeably. Because of the cross-track scanning of these sensors, the satellite footprints are 15 to 25 km in the largest dimension



Algorithm development (Clustering approach)

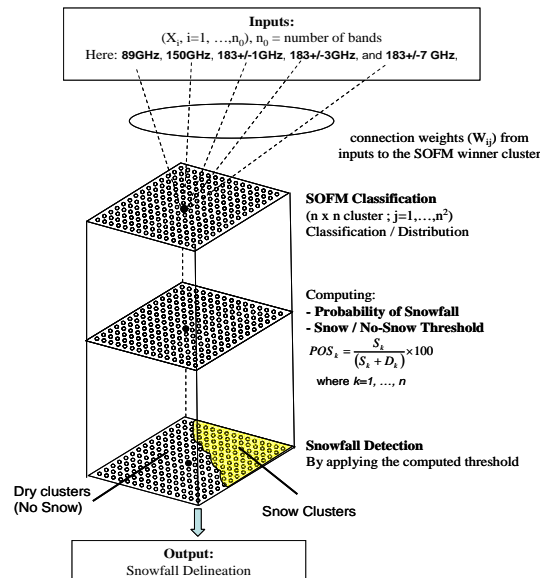
The algorithm processes high frequency radiometer channels and assigns snow/no snow flag to each pixel by 1) classifying input vectors using the Self-Organizing Feature Map (SOFM, Kohonen, T., 1982) method; 2) calculating the probability of snowfall for each classified group (cluster); 3) defining a proper threshold to distinguish snow and no-snow clusters. The proper threshold is fixed with the aid of the probability matching technique (Cheng, et al., 1995). Using this technique, a critical probability threshold (CPT) is computed. CPT distinguishes clusters most likely associated with snow event from those likely to represent no-snow situations.

Training the SOFM occurs in unsupervised mode without the introduction of snow/no-snow observations into the process. The unsupervised training improves the SOFM classification by reducing the confusion that may result from uncertainties in precipitation-measurement field. Below is a brief description of the procedure, which is described in more details in the previous study (Hsu et al., 1999).

SOFM divides the multi-dimensional feature space into a predetermined number of clusters. These clusters are arranged into a two-dimensional discrete map which preserves the topological order of feature vectors; meaning that features within each cluster retain the same order in which they were introduced to the network. The network has two fully connected layers: an input layer and a competitive layer.

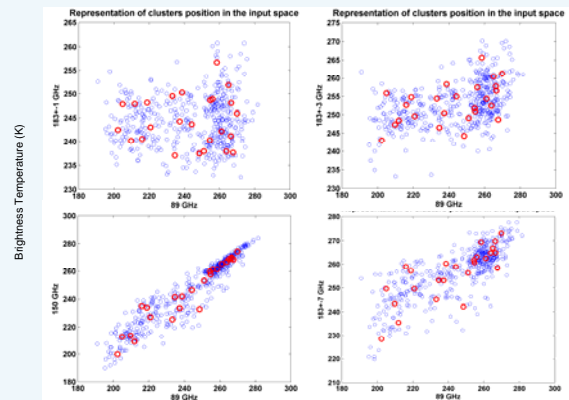
The process of training consists of presenting input vectors one by one from the training dataset to the network. The input vectors (i.e., training dataset) are randomly sampled from the dataset allocated to algorithm development. The input vector is normalized in each input dimension to transform the features into the same scale. According to the shortest distance (d) between each normalized input vector ($x_i, i=1, \dots, n_0$) and the SOFM cluster center and through a recursive process of competitive cluster selection and weight adjustment, the locations of the clusters' centers become stable

Schematic overview of the algorithm



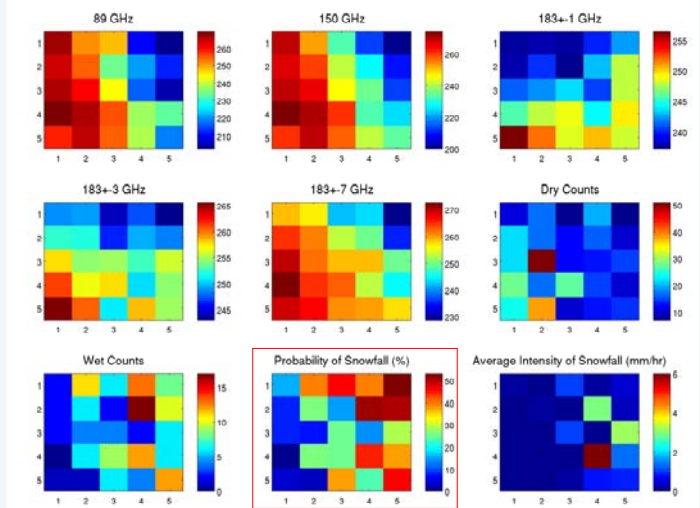
Input preparation, which must be carried out prior to classification includes: (a) removal of AMSU-B/HMS data points that are beyond viewing angle threshold (here in selected as $\pm 55^\circ$), (b) performing a preliminary filter to allow SOFM to allocate more snow clusters to snow possible situation (e.g. excluding obvious no-snow pixels), and (c) input vector normalization.

Results: Exploratory Analysis



The fixed cluster centers (red circles), with predefined numbers, are representative for a group of input vectors (blue circles) having similar properties.

After training, the trained SOFM has the ability to assign any arbitrary feature vector (blue circle) to a SOFM cluster (red circle) according to their minimum distance.



- 25 clusters, arranged in a 5x5 2D feature map is used in this study.
- Training Set (600pts): POD=66%, FAR=55%, BIAS=149, ETS=0.2
- Validation set (280pts): POD=62%, FAR=58%, BIAS=150, ETS=0.16

Conclusion

- The proposed algorithm uses SOFM technique, which transforms inputs of arbitrary dimension into a two dimensional discrete map with neighborhood-preserving constraint. This allows the algorithm to assess the inter-relationship between input channels and observation (here snowfall) and gives insights toward understanding the most snowfall-relevant input features. By calculating the probability of snowfall in each cluster and using probability matching method a snow/ no-snow threshold is defined, which can be used in the validation period.
- Results of this study show that 89 GHz, 150 GHz, 183GHz bands are useful for snow detection. No clear relationship between snowfall and 183+/-1 band was obtained. GMI will have these High frequency channels, thus this method can be applied during GPM operations, with no dependency on model derived inputs.
- More investigation is needed to evaluate the capability of this method in different seasons and regions.

Future Work

- Collect large spatial and temporal data sets to further refine the algorithm
- Investigate the regional and seasonal performance of the algorithm
- Extend the algorithm from binary snow/no-snow classification to snowfall amount.
- Investigate the effects of using AMSU-B and MHS interchangeably on the accuracy of the algorithm and develop mechanisms to address such impact

References

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